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A case study in smart manufacturing: predictive analysis of cure cycle results for a composite component

Micaela Lucia Bangerter[1], Giuseppe Fenza[1], Mariacristina Gallo[1], Alberto Volpe[1], Gianfranco Caminale[2], Nicola Gallo[2], Fabrizio Leone[2]

[1]Dipartimento di Scienze Aziendali - Management & Innovation Systems, University of Salerno, Fisciano (SA) 84084, Italy.
[2]Leonardo Spa, Via Tiburtina Km. 12, Roma RM 00156, Italy.

Correspondence to: PhD. Mariacristina Gallo, Dipartimento di Scienze Aziendali - Management & Innovation Systems, University of Salerno, Via Giovanni Paolo II 132, Fisciano (SA) 84084, Italy. E-mail: mgallo@unisa.it

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Abstract

Aim: This work proposes a workflow monitoring sensor observations over time to identify and predict relevant changes or anomalies in the cure cycle (CC) industrial process. CC is a procedure developed in an autoclave consisting of applying high temperatures to provide composite materials. Knowing anomalies in advance could improve efficiency and avoid product discard due to poor quality, benefiting sustainability and the environment.

Methods: The proposed workflow exploits machine learning techniques for monitoring and early validating the CC process according to the time-temperature constraints in a real industrial case study. It uses CC's data produced by the thermocouples in the autoclave along the cycle to train an LSTM model. Fast Low-cost Online Semantic Segmentation algorithm is used for better characterizing the time series of temperature. The final objective is predicting future temperatures minute by minute to forecast if the cure will satisfy the constraints of quality control or raise the alerts for eventually recovering the process.

Results: Experimentation, conducted on 142 time series (of 550 measurements, on average), shows that the framework identifies invalid CCs with significant precision and recall values after the first 2 hours of the process.

Conclusion: By acting as an early-alerting system for the quality control office, the proposal aims to reduce defect rates and resource usage, bringing positive environmental impacts. Moreover, the framework could be adapted to other manufacturing targets by adopting specific datasets and tuning thresholds.

Keywords: Deep learning, LSTM, time-series forecasting, decision support systems, anomaly detection, Industry 4.0., sustainability

INTRODUCTION

Phenomenons such as Industry 4.0, the Internet of Things, and Smart Manufacturing allow the spreading of smart technologies in manufacturing areas. The increasing amount of data enables the use of Machine Learning algorithms to design tools that support decision-makers in daily activities and predict emerging situations. Many opportunities arise for extracting insightful information from the manufacturing processes to optimize production and avoid defects in the quality of the final product. Therefore, early anomaly detection and trend prediction in production line assets are widespread research topics. Furthermore, anomaly and fault detection in manufacturing contexts can considerably reduce manufacturing defects, thus decreasing the negative environmental impact that this may cause (e.g., energy consumption for products not reaching quality specifications and to be discarded)[1]. In this sense, experts agree that the Industrial Internet of Things (IIOT) framework can support important sustainability goals regarding innovation and responsible consumption and production[2].

Anomaly detection aims to identify outliers in the dataset, identifying patterns in data that do not follow the expected behavior. In particular, the literature introduced three categories of anomalies[3]: point, contextual, and collective. Point anomalies occur when a single point is considered abnormal against the entire dataset. Contextual anomalies are data points considered abnormal only under certain context attributes. Finally, collective anomalies occur when a collection of points can be considered abnormal against the entire dataset. This work exploits the second category of anomaly detection to establish the validity of a process consisting, in turn, of multiple time series coming from different sensors, and that depends on numerous conditions.

From a different point of view, the literature also suggests annotating sensor data semantically to improve its monitoring[4–6].

Anomaly detection techniques range from the more classical statistical approaches[7] to the most recent deep learning models[8]. Furthermore, since production line data often consists of sensor observations represented by time series (e.g., temperature measurements), applications often regard time series forecasting. For example, given a vector of historical values $\{t_1, t_2, ..., t_n\}$, forecasting future values $\{t_{n+1}, t_{n+2}, \ldots\}$ based on them. Then, predictions can be exploited for anomaly detection purposes[9].

As recently asserted by Pittino *et al.*[10], despite the quantity of literature research on anomaly detection in manufacturing, methodologies and techniques often need to be re-adjusted and tested in real conditions, with costs in model recalibration with an increasing overhead and higher probability of model errors. Starting from such situations, this work aims to fulfill concrete requirements of the aerospace industry to realize an early-alerting system for identifying incorrect processes that can bring in non-compliant final composite materials. In these types of manufacturers, the quality of composite materials is essential due to their subsequent adoption purposes.

In line with many recent approaches in the literature, this work adopts a long short term memory network (LSTM) considered particularly suitable for anomaly detection in a streaming context due to its forecasting capacity[9,11,12]. Moreover, models such as the autoregressive integrated moving average (ARIMA), extensively using statistical methods for time series forecasting, were unsuitable for the examined context. Managing many time series from different temperature sensors needs a model that considers them all together. In this sense, Siami-Namini *et al.* demonstrated the superiority of LSTM with respect to ARIMA in time series forecasting[13].

The proposed methodology is a case study regarding the cure cycle (CC) process at Leonardo s.p.a. It collects historical temperatures, annotates them through the fast low-cost online semantic segmentation (FLOSS) algorithm (which identifies the main trend changes in series themselves), and trains a LSTM trying to predict future temperatures. The framework uses predicted temperatures to identify anomalies in the time series and establish if the entire process could be considered invalid. Experimental results reveal promising performance: already after the first 2 hours, the algorithm suggests the presence of irregularities in the CC with good reliability (measured in terms of Precision and Recall). Moreover, such reliability achieves optimal level after the first 3 hours of the cycle.

The rest of the paper is organized as follows. First, the state-of-the-art is exposed in the Related Works Section. Next, the Methods includes: (i) a description of the reference context; (ii) an overview of adopted theories; and (iii) details of the proposed methodology. The specification of scenarios executed during the experimentation, together with adopted data, measures, and results, in terms of corrected identified invalid cures, are presented in the Results Section. Finally, the Discussion Section discusses and concludes the work.

RELATED WORKS

Anomaly detection is crucial for ensuring quality in the final manufacturing product and preventing products from being discarded. The presented approach implemented in this work, combined with experts' criteria, classifies the cure cycle as valid or invalid.

Techniques for detecting anomalies range from the classical statistical approaches to the use of deep learning in the recent literature. This section explores the state-of-the-art in these areas.

Principal component analysis (PCA) is one of the statistical approaches for selecting the most important features responsible for the highest variability in the input dataset. It has been implemented to detect anomalies in-process monitoring, including the production through autoclaves. For example, Park *et al.* used weighted PCA by combining PCA with slow feature analysis (SFA) for anomaly detection in low-density polyethylene manufacturing processes[14]. Arena *et al.* present the anomaly detection applied to a photovoltaic production factory scenario in Italy using the Monte Carlo technique before applying PCA. They successfully anticipated a fault in the equipment with an advance of almost two weeks[15].

Deep learning is widely adopted for anomaly detection in different areas, such as seismic event detection[16], attack of industrial control systems discovery by network traffic monitoring[17], and digital health[18]. Regarding the aviation field, anomaly detection has recent advances[19]: RNN is widely applied, especially LSTM, to analyze time-series data. For example, Nanduri *et al.* implemented an LTSM with gated recurrent units to perform anomaly detection for aircraft flights with powerful performances[20]. Mori used a simplified version of LSTM, GRU, to identify untypical flight landings[21]. For more general purposes, Ding *et al.* proposed a real-time anomaly detection algorithm based on LSTM and Gaussian mixture model (GMM) for multivariate time series[22] that was validated over a dataset with many types of anomalies coming from stream data.

Machine and deep learning approaches are also largely adopted in the manufacturing area. Lejon *et al.*[23] address different machine learning methods utilizing data from industrial control systems suitable for detecting anomalies in the press-hardening process of automotive components. Petkovic[24] supported the prediction of the quality process of laser welding with computational intelligence techniques, specifically support vector regression (SVR). Quatrini *et al.*[25] presented an anomaly detection framework with real-time data from a specific multi-phase industrial process that can guarantee high-performance results. In terms of temperature optimization, Carlone *et al.*[26] proposed a solution based on artificial neural networks to predict the composite temperature profile during the autoclave curing process. Other sustainable manufacturing attempts regarded energy optimization[27,28] and material efficiency[29]. The paper in[30], similarly to the proposal, aims to reduce defects for more sustainable productivity.

Beyond anomaly detection solutions, the recent literature also focused on optimizing the composite autoclave process and improving the resulting products[31,32]. Golkarnarenji *et al.* studied a prediction model combining SVR with a genetic algorithm (GA) to reduce energy consumption in carbon fiber manufacturing[33]. There is also an extensive adoption of LSTM in manufacturing for predictive maintenance, anomaly detection and quality prediction[34–36]. However, to the best of our knowledge, no contributions are combining the FLOSS algorithm with LSTM for time series segmentation.

As already mentioned in the Introduction Section, this work fulfills the concrete requirements of an aerospace industry to realize an early-alerting system to identify incorrect processes that can bring in non-compliant final composite materials by exploiting forecasts from a deep learning model.

METHODS

This section introduces the theoretical background and describes the methodology and the application context.

Application context

This work originated from the authors' participation in the Leonardo 4.0 project promoted by Leonardo s.p.a. It intends to support digital transformation in the manufacturing sector to increase efficiency and scale down production times and expenses in order to improve its sustainability. Among proposed challenges, the CC analysis task requires a system that facilitates operators' work during the analysis of cure cycles.

A cure cycle is an autoclave manufacturing process. An autoclave is used to perform industrial operations that require controlled high temperatures and pressures. It is often used in industrial applications in composite manufacturing. For example, autoclaves are generally used in airplane parts production due to their capacity to ensure high quality for composite structures.

CC process is monitored through multiple thermocouples (up to 60-70 sensors) connected to the autoclave controllers, which record the temperatures reached at several points for the entire treatment period:

- Inside the carbon fiber package;
- On the tool;
- Inside the autoclave.

The process is completed successfully if certain validation specifications are met (e.g., attaining certain temperature ranges for specific time intervals). Requirements are associated with product categories that the company treats. For example, validation specifications could require that: when the temperature is between 172 and 182 Celsius degrees, the heating rate must be between 0.6 and 2.8 Celsius degrees per minute. If the specifications are not met, the cure cycle obtains negative results, and the product must be discarded.

In this context, individual item data outside the normal range is considered an *anomaly*. Nevertheless, a single anomaly does not necessarily affect the validation of the entire cure cycle. This decision depends on the pres-

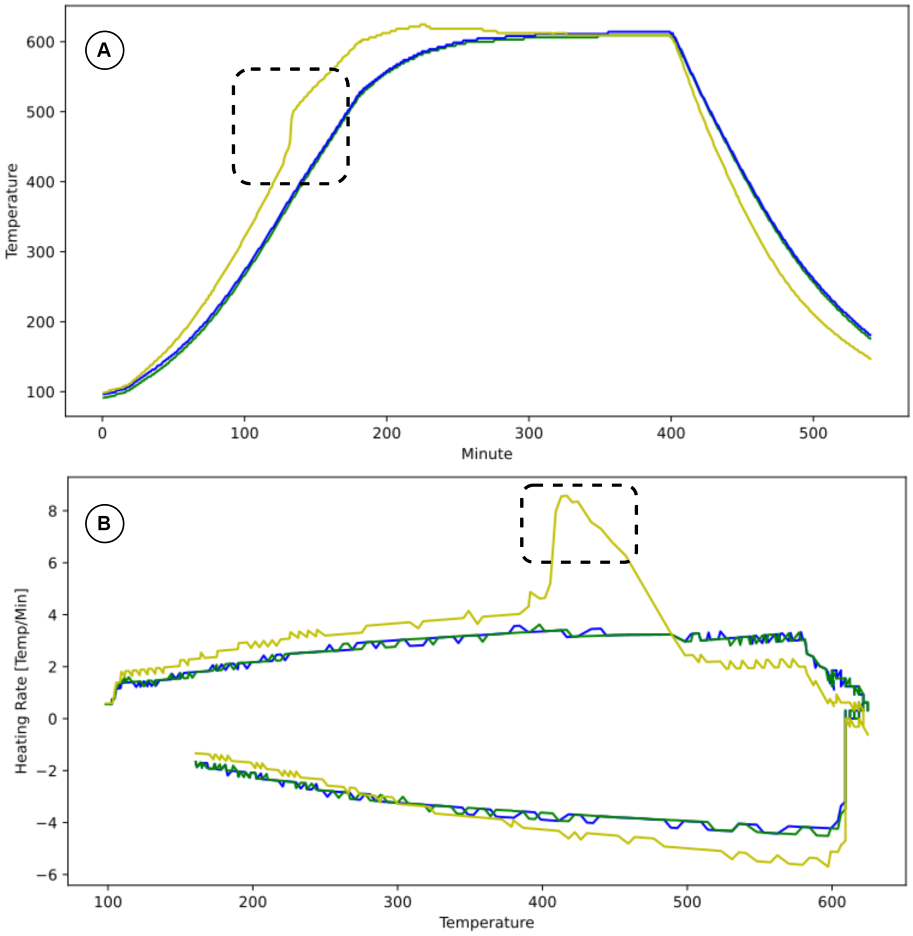

Figure 1. Example of cure cycle results. A: Temperature time series; B: rates diagram.

ence of multiple anomalies. Usually, a quality control officer analyzes data made available by the autoclave at the end of the process and makes a decision.

As mentioned earlier, the validity of a cure cycle mainly resides in the compliance of *heating rates* (for the sake of brevity, rates) against specifications given by experts or customers. The rate identifies the growth or degrowth intensity of temperatures; it is calculated with a backward step (or forward step) of n minutes. In particular, assuming that t_i is the actual temperature, with a backward step, the rate is evaluated through Equation (1).

$$Rate = \frac{t_i - t_{i-n}}{n} \tag{1}$$

For better interpretation, let us show an example of the process made by the quality control officer. Curves in Figure 1A depict temperatures revealed by three different sensors of a specific cure cycle that the officer acquires and analyzes. By observing the graph, the operator can identify anomalous temperatures for the yellow series at different points. Analogously, curves in Figure 1B, which depict rates for the same series and help the operator analyze curves, highlight an uncommon trend for the yellow series. Based on the quantity and quality of existing anomalies, the quality control officer decides if invalidate the cure cycle.

The objective of the proposed framework relies on assisting the officer during the validation, acting as an early-alerting system in the specific scenario. The framework works as follows. Firstly, it uses historical time series from cure cycles to train a regression model to predict future temperatures. Then, an online system monitors temperatures, forecasts them for the coming 25 min, and simultaneously compares predicted rates against requested ones. Whenever a discrepancy is identified, the operator is alerted. This way, it is possible to anticipate the *anomaly* for up to 25 min. Moreover, the system is adjusted through specific thresholds to classify the overall cure cycle very early. In fact, it compares all series forecasts with rate specifications and establishes when the overall process will fail. This additional functionality avoids a single sensor drift or failure invalidating the cure cycle. Still, it is mandatory to understand the work of other sensors. Practically, the system allows monitoring of the process in real-time to understand eventual failure or downtime of specific sensors and, in parallel, can decide, with anticipation, if the process will fail.

Let us demonstrate the functionality of online anomaly detection with an example. Figure 2 shows the procedure executed at the instant i. The regression model predicts, taking advantage of the previous 10 temperatures, the following 25 for each series (see subfigure 2A). For each made prediction, starting from the temperature t_i, the rate is calculated by comparing it with t_{i-10} following Equation (1) (with a backward step of 10 min, see subfigure 2B). When the computed rate does not meet the validation specifications (i.e., does not fall in the range between *MIN LIMIT* and *MAX LIMIT* of subfigure 2B), a single anomaly is detected at instant i. The yellow series in subfigure 2B shows a set of anomalies due to rate values greater than the maximum allowed by the specifications. As one or more anomalies are identified, the framework compares the number of seen anomalies for all considered sensors to specific thresholds to establish the validity of the cure cycle. As soon as these anomalies are detected or exceed thresholds, the framework alerts the officer that can make decisions about the ongoing cycle without waiting for its end.

Theoretical background

This subsection describes the background theories and concepts relevant to understanding the proposed methodology.

Long short term memory network

The LSTM[37] is a type of recurrent neural network (RNN). These networks can only keep a few previous stages in a sequence, making them ineffective for preserving longer data sequences. To undertake it, LSTM has additional features to memorize data sequences. A typical LSTM structure consists of a set of recurrently connected subnetworks, known as memory blocks. Each block is configured mainly by memory cell state, forget gate, input gate, and output gate. The central element, the memory cell, runs through the entire chain of blocks to add or remove information to the cell state with the support of gates. The forget gate decides what relevant information should be thrown away or kept. The input gate determines if it should update the information stored in the memory. Finally, the output gate learns when the stored information should be used. The structure of a memory block with one cell is shown in Figure 3.

The LSTM network works by identifying the correlation between the input and the output. Giving an input $x = (x_1, ..., x_t)$, it calculates the network unit activation by iteratively processing the equations:

$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \tag{2}$$

$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \tag{3}$$

$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \tag{4}$$

$$\tilde{c}_t = \sigma_c(W_c x_t + U_c h_{t-1} + b_c) \tag{5}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot c_t \tag{6}$$

$$h_t = o_t \odot \sigma_c(C_t) \tag{7}$$

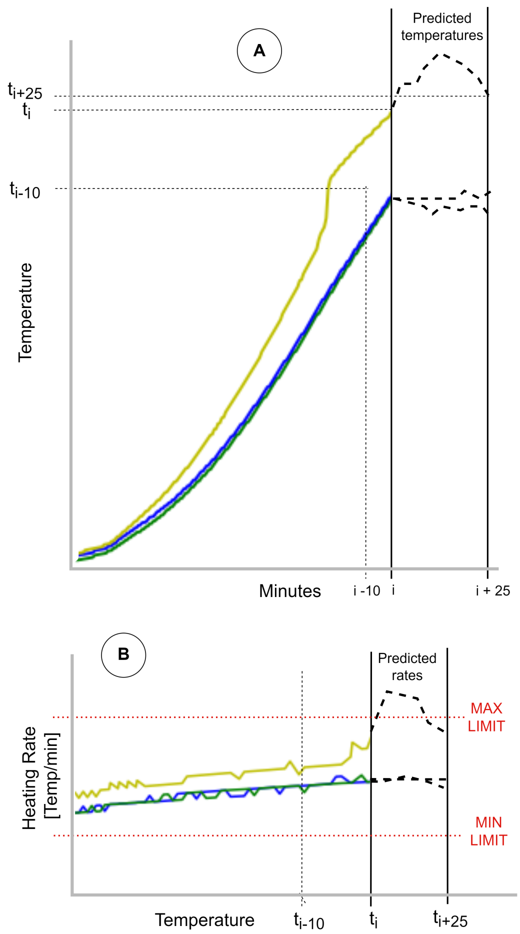

Figure 2. Example of anomaly detection at instant i. A: predicted temperatures until instant $i + 25$. B: corresponding rates compared with specifications.

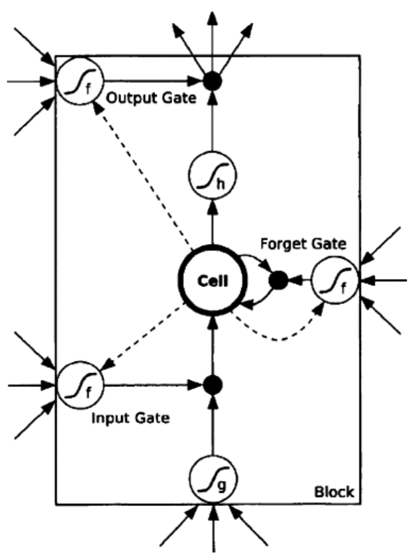

Figure 3. Structure of LSTM memory block with one cell[38].

where the initial values are $c_0 = 0$ and $h_0 = 0$; W, U and b denote, respectively, the weights of the input and recurrent connection and the bias vectors. Their subfix indicates the correspondence to the gate: i the input gate, o the output gate and f the forget gate and c the memory cell. These last three parameters are the ones that need to be learned during the training. σ_g represents the sigmoid activation function, σ_c the hyperbolic tangent activation function, $\odot$ the Hadamard product (element-wise product) of the vectors, f_t, i_t, o_t and $\tilde{c}_t$ the activation vectors of each gate, c_t the cell state vector and h_t the LSTM unit's hidden state vector, also known as the output vector.

LSTM has been chosen for the regression aim in this work due to its ability to process the overall data sequence, preserving important information.

Time series segmentation

Time series segmentation splits the series into homogeneous segments. It is used to add context information to time series. In particular, it establishes if temperatures undergo relevant changes (e.g., from the heating phase to stasis).

Among available segmentation models, three types can be identified: shape, statistic, and probabilistic methods. Statistical approaches use slope, mean, minimum or maximum metrics to identify segments. The probabilistic approach estimates segments based on the probability that a sample belongs to the same or a new segment. Finally, the shape approach uses the time series shape by resembling human viewing a plot [39]. This last model is implemented in this work; specifically, FLOSS is adopted [40].

FLOSS is a domain agnostic technique included in the STUMPY library, used for data mining in time series. It efficiently computes the matrix profile that keeps the z-normalized Euclidean distance between its nearest neighbor and any subsequence within the time series. FLOSS exploits this matrix and produces a companion time series called the Arc Curve (AC), which annotates the raw time series with information about the likelihood of a regime change at each location. The AC is essentially a pointer from an index to its nearest neighbor in the matrix index vector. The premise is that similar patterns should be included within the same regime and that the number of arc curves pointing between different regimes should be few. For example, using a time series with two regimes, the split would be where the minimum number of arc curves exists. However, this method has an edge situation in which no arc will live in the first sample in the time series. For this reason, the beginning of the time series must be compensated to not perform the segmentation at this point. So, the Corrected Arc Crossings (CAC) is defined as a metric of the number of overarching arc curves with the corrections for the edges, and as it is concerned with streaming data is strictly one-directional rather than bidirectional for the case of batch data. This metric is in the interval $[0, 1]$, where a low value is few overarching curves, and high values are many. Figure 4 shows an example from a cure cycle sensor that measures temperatures. The image shows how the algorithm is able to identify a change in the series.

Cure cycle validation methodology

The proposed solution mainly consists of two macro-phases. In the first one, a regression model (i.e., LSTM Neural Network) is trained through historical data from the cure cycle process in the aerospace industry. Then, the cure cycle validation phase exploits forecasting made by the LSTM generated in the previous step to validate the CC. This section details each phase.

LSTM neural network training

In this phase, a dataset of historical data of 5 types of composite material production is firstly pre-processed to adapt its format to the model input. In particular, the last 10 temperature values (i.e., $\{t_{i-1}, t_{i-2}, \ldots, t_{i-10}\}$) are inputted to the FLOSS algorithm, which returns a flag in $(0, 1)$ as the semantic information about regime change associate to the series section. Finally, this information is attached to temperatures and inputted into

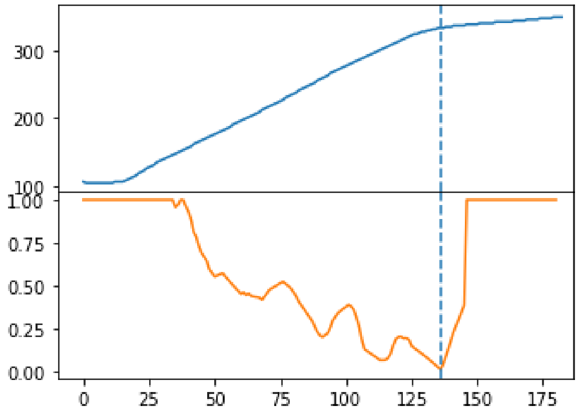

Figure 4. Example about temperature time series and corresponding CAC graph: a change is identified at minute 136.

the model. The output layer produces a vector of 8 values representing the predictions at the following instants: $\{t_i, t_{i+1}, t_{i+2}, t_{i+5}, t_{i+10}, t_{i+15}, t_{i+20}, t_{i+25}\}$.

The adopted LSTM has the following structure: one input layer, a hidden LSTM layer of 64 neurons with the default sigmoid activation function, followed by a dropout of 0.3 and, finally, an output layer that makes the prediction. The model training was compiled with a mean squared error (MSE) loss function to calculate the difference between real and predicted values and with Adam optimizer using the default learning rate. Details about achieved performance are reported in the Results Section.

Cure cycle validation

At each timestamp (i.e., minute), temperatures forecasted by the model trained in the previous phase are adopted to establish whether the anomaly will occur. More in detail, at each timestamp i, the framework passes to the LSTM model the last 10 temperatures and the FLOSS information at that instant. As a result, the model produces the prediction of 8 values that reaches 25 min after i (i.e., the forecasts). For each forecast, a rate is calculated with a backward step of 10 min[1] by utilizing the temperature value at the $10th$ precedent minute and the predicted value. The rate values are then validated through the *Cure Verification Algorithm*.

Essentially, the cure cycle validation phase can be summarized as follows (see Figure 5):

- Last 10 temperatures are input for the FLOSS algorithm;
- The FLOSS output, together with the last 10 temperatures, is submitted to the LSTM model;
- The LSTM model forecasts up to 25 min ahead;
- Forecasts are input for heating rate calculation. Such values measure the increase or decrease rates of curves and are explicitly adopted by experts to make cure cycle validations;
- The Cure Verification Algorithm compares future rates with experts' criteria, decides if an operator needs alerting by comparing the number of anomalies with fixed thresholds, and classifies the cycle as valid or invalid.

Cure Verification Algorithm

The proposed Cure Verification Algorithm, mainly responsible for the cure cycle validation, is shown in Figure 6.

[1] This value derives from validation criteria.

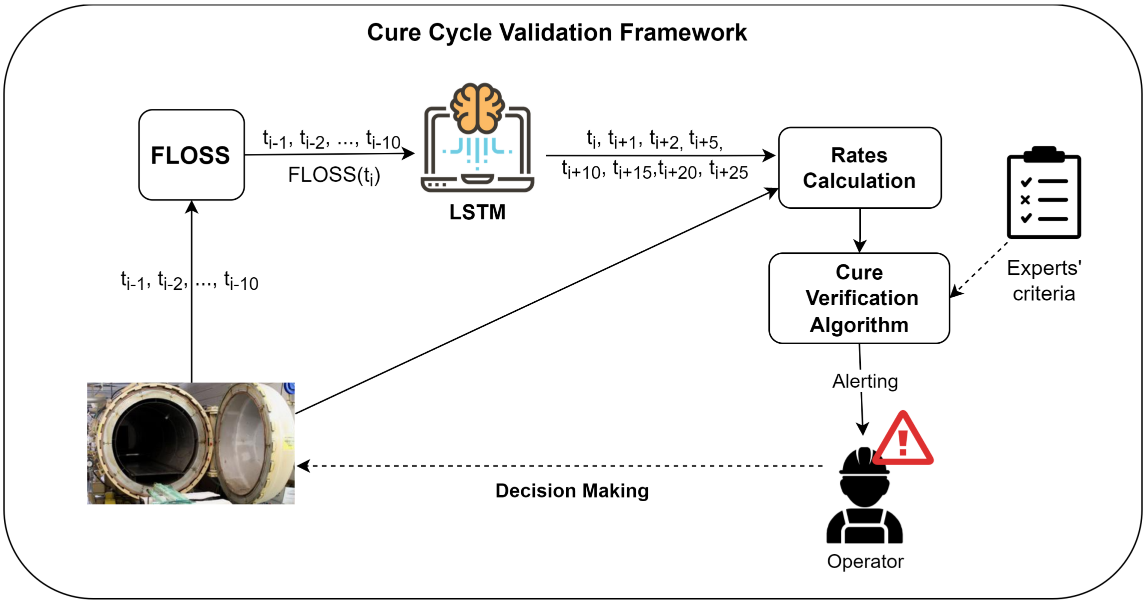

Figure 5. Cure Cycle Validation workflow.

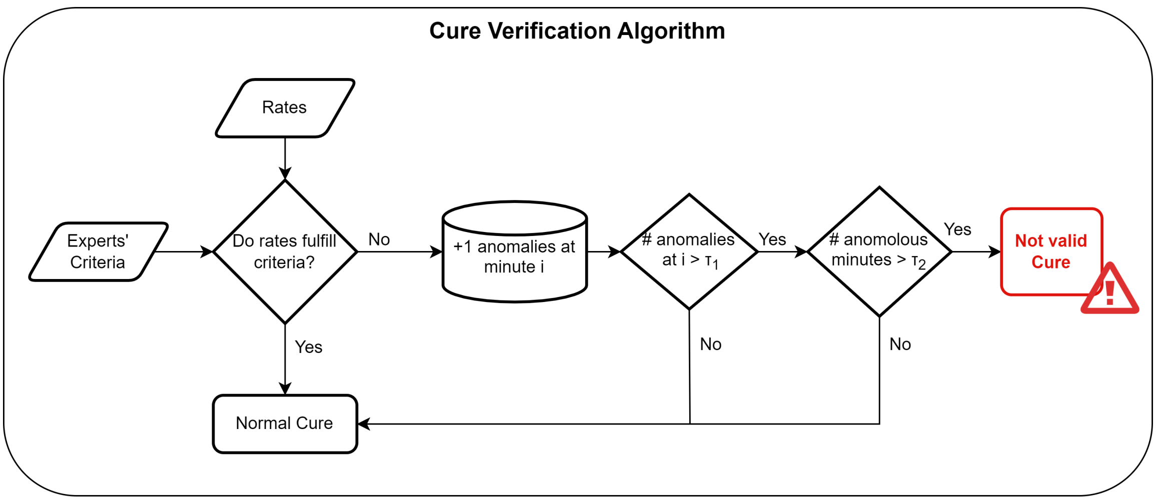

Figure 6. Cure Verification Algorithm.

Let us start again distinguishing between *anomaly* and *invalid cure cycle*. The first is identified when a difference between predicted rates and experts' criteria arises. Conversely, a cycle is considered invalid when the number of anomalies exceeds specific thresholds. In this sense, two defined thresholds measure, respectively, the number of recognized anomalies at each instant i (i.e., τ_1) and the number of instants for which there are more than τ_1 anomalies (i.e., τ_2). So, the algorithm makes the following checks:

- At each instant i, the rate evaluated through real and predicted temperatures is compared with the defined experts' criteria. If criteria are not passed, the number of anomalies for the minute i is incremented.
- At each instant i, the number of minutes N having more than τ_1 forecasted anomalies is compared with τ_2. If $N > \tau_2$, the operator is alerted about the *invalid cure cycle*.

RESULTS

This section details the experimentation carried out to evaluate the proposed framework in terms of invalid cure cycle identification, on real data. The following sections describe the adopted dataset, evaluation measures, and validation processes.

Data description

The adopted dataset consists of time series deriving from the application of multiple cure cycles by Leonardo s.p.a. regarding composite materials in the aeronautic context. In particular, for training, the LSTM model and the process of cure cycle validation are used 142 cure cycles, some of which are considered invalid according to experts' ground truth.

Evaluation

As discussed in the previous section, the proposed framework consists of two main phases that must be evaluated separately. Thus, different approaches are selected for the evaluation of the overall framework. Regarding the LSTM neural network training, the evaluation adopts the MSE metric, which is useful to measure the difference between real and predicted values and is defined as Equation (8)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(t_i' - t_i)^2 \tag{8}$$

where t_i' is the predicted value, t_i is the real temperature value in the test set, and n is the number of predictions.

In terms of invalid cure identification, classical metrics of Precision and Recall are adopted. They are defined as follows:

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

$$Recall = \frac{TP}{TP + FN} \tag{10}$$

where TP is the number of invalid CCs present in the set correctly recognized by the framework, FP is the number of invalid CCs detected by the framework but not recognized as invalid, and FN is the number of invalid CCs present in the set but not recognized by the framework.

Evaluation procedures

The framework analyzed 142 curves, and different scenarios were fulfilled. The objective was to find the best combination of thresholds and validation parameters to obtain the best Precision and Recall in terms of correctly identified invalid cures. The analysis was made in three instants (namely, milestones) of the process, after the first hour and one-hour intervals: 60, 120, and 180 min. However, since the quantity of information was insufficient for the framework to correctly recognize invalid CCs after the first hour, the following results do not consider the aforementioned milestone. Moreover, three different scenarios are assessed:

- The first execution was made using experts' criteria as-is. Regarding τ_1 and τ_2 thresholds, the method considers significant anomalies identified at least 4 times in the same minute (i.e., $\tau_1 = 4$); the total number of anomaly minutes (i.e., τ_2) was set to 8.
- A variation of the previous execution consists in allowing a slight deviation in the experts' criteria. Precisely, maximum and minimum limits for the heating rates were modified with ±0.2 to reduce false negatives. Additionally, the number of anomalies necessary to identify invalid cures (i.e., τ_2) was increased to 12.
- The last scenario is a further variation of the previous one. At the first milestone (i.e., 120 min), not yet revealed anomalies (i.e., regarding the next minutes in the time series) are not considered for the Recall evaluation: they do not contribute to FN calculation. The reason is that the framework can only decide about the actual situation: previous temperatures and the next 25 predicted minutes.

The following subsection summarizes the results of each scenario.

Table 1. A summary of scenarios and their results

Scenario	Experts' criteria	τ_1	τ_2	120 min		180 min	
				Precision	Recall	Precision	Recall
$Scenario_1$	as-is	4	8	0.57	0.72	0.40	0.86
$Scenario_2$	±0.2	4	12	1	0.46	0.82	0.88
$Scenario_3$	±0.2	4	12	**1**	**0.8**	**0.82**	**0.88**

Outcomes

Regarding the first phase of the methodology, namely the LSTM training, the value of achieved MSE is 0.0067 Fahrenheit degrees. It follows that the regression model forecasts future temperatures with a good level of reliability. This aspect is particularly relevant for the subsequent adoption of forecasts for the cure cycle validation.

Regarding the second phase, the cure cycle validation, Table 1 describes the results of each scenario. Considering criteria as-is in the first scenario produces many false positives (FP) and a low true positives (TP) value. In the second scenario, combining a higher level of τ_2 with more flexible experts' criteria contributes to better results in Precision for the first milestone and Precision and Recall for the second milestone. Finally, in the third scenario, as previously discussed, not considering future anomalies in the TP and FN evaluation contributes to achieving the best results already at the first considered milestone.

DISCUSSION

The spread of Industry 4.0 allowed manufacturers the adoption of new technologies (e.g., smart sensors). Such equipment produces a consistent amount of real-time data that gives many data analysis opportunities that could feed learning models or decision support systems.

This work, developed during activities of the project Leonardo 4.0, proposes an early cure cycle validation based on a deep learning model through real data. First, an LSTM is trained with historical data regarding a cure cycle for composite material production from autoclaves. The resulting model predicts future temperatures at each step (i.e., minute) and compares them with validation criteria. Through that criteria, the system continuously monitors process data and early informs the quality control officer about drifting series (regarding specific sensors) or, more in general, of inadequateness of the ongoing cure cycle. The officer can decide to make suitable decisions that can positively impact not only the production time and the final product, but also the environment.

Experiments made on a real dataset provided by Leonardo s.p.a. reveal a good capacity of the framework to discern between valid and invalid cures with consistent anticipation.

Although the proposal experimented with a single case study, the LSTM originally used the output of the FLOSS algorithm as the contextual information of the time series. This choice and the exhibited performance support the hypothesis that the method can be used in other contexts tuning thresholds and providing other time series.

DECLARATIONS

Authors' contributions

All the authors have participated in the research work and contributed to this manuscript.
All the authors have read and approved the final manuscript.

Availability of data and materials
Not applicable.

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Conflicts of interest
All authors declared that there are no conflicts of interest.

Ethical approval and consent to participate
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Consent for publication
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